Hybrid Handover Decision Using Neuro-Fuzzy Logic Approach for Heterogeneous Wireless Networks

Suviraya thongthep
Department of Electrical Engineering, Faculty of Engineering, Srinakharinwirot University, Thailand

Wekin Piyarat
Department of Electrical Engineering, Faculty of Engineering, Srinakharinwirot University, Thailand

Sunisa Kunarak*
Department of Electrical Engineering, Faculty of Engineering, Srinakharinwirot University, Thailand

ABSTRACT

This paper decides about the vertical handover which is a significant process in the fifth generation (5G), using neuro-fuzzy logic that works between artificial neural network and fuzzy logic of heterogeneous wireless networks has 3 categories as Wireless Local Area Network (WLAN), Long Term Evolution-Advanced (LTE-A), and Mobile Worldwide Interoperability for Microwave Access (Mobile WiMAX). In addition, determine parameters affecting the handover decision of wireless communication such as received signal strength (RSS), mobile speed, and bandwidth to enter the handover decision process of neuro-fuzzy and the simulation of a structure uses data measured from parameters. The conditions of handover decision are threshold value and dwell time that prevent connection quality and unnecessary handover from decreasing. The purpose of this paper is to make users satisfied with the quality of service (QoS) and reduce the number of handovers and blocked calls. The research result found that the neuro-fuzzy algorithm has better performance when compared with fuzzy logic and back-propagation neural network methods. Consequently, the neuro-fuzzy illustrates the number of handovers and the number of blocked calls on average decrease by 38% and 26% when compared with the back-propagation neural network and decrease by 59% and 36% when compared with the fuzzy logic method, respectively.

CCS CONCEPTS

• **Mobile and ubiquitous calculations**; • **Mobile networking and systems**; • **QoS in networks**;

KEYWORDS

Dwell time, Heterogeneous wireless networks, Neuro-fuzzy, Quality of service

ACM Reference Format:
Suviraya thongthep, Wekin Piyarat, and Sunisa Kunarak. 2023. Hybrid Handover Decision Using Neuro-Fuzzy Logic Approach for Heterogeneous Wireless Networks. In *2023 the 12th International Conference on Networks, Communication and Computing (ICNCC) (ICNCC 2023), December 15–17, 2023, Osaka, Japan.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3638837.3638840

*Corresponding Author

ICNCC 2023, December 15–17, 2023, Osaka, Japan

ACM ISBN 979-8-4007-0926-5/23/12.
https://doi.org/10.1145/3638837.3638840

1 INTRODUCTION

Nowadays, telecommunications technology has been developed that is significant in our daily lives, it contributes to pushing various businesses in occurrence and affects the development of the nation. Wireless communication technology has developed continuously into the fifth generation (5G) that improves usability to be more efficient and stable. To reduce problems with system delays or internet crashes because it is used for work that requires high accuracy and fewer errors, this generation focuses on the speed of data transmission. However, the fast development helps to increase users, but the limited channels affect dropped calls or blocked calls. Thus, the procession of changing the communication channel from the active channel in a current cell to the channel of a neighboring cell within the wireless network is very important because this one ensures continuity and good quality for users. As the user moves away from the base station that is used, the received signal strength will gradually decrease. On the other hand, the received signal strength close to the base stations will increase. The system must forward timely communication services before a signal is lost, this processing is called the handover. Changing channels within the same network technology is called the horizontal handover (HH). Conversely, the vertical handover (VH) uses a different network technology. The process is significant for future communication, many researchers have proposed the vertical handover decision. Therefore, the hybrid handover decision using a neuro-fuzzy logic approach for heterogeneous wireless networks is another interesting method for the handover decision.

The author uses dwell time to reduce the burden of handover before entering the neuro-fuzzy process. Dwell time helps reduce the ping-pong effect, which refers to several handovers that happen back and forth between two Access Points (APs). This takes a severe disadvantage on the quality of service (QoS) and the network load. Hence, this paper brings various factors affecting the handover decision as proposed. The number of handovers and the number of blocked calls were reduced, to receive more service quality.

2 RELATED WORK

The vertical handover decision using the fuzzy logic (FL) method for the fourth generation (4G) that has WLAN and LTE. The input parameters such as RSS, network coverage, bandwidth, and quality of service (QoS) have latency, jitter, and packet loss. The selection of network uses the fuzzy multiple attribute decision making algorithm (FMADM) and finds results from the fuzzy Inference System (FIS) using Mamdani model. So, the experiments showed that using fuzzy logic reduces time and complexity in systems that need to consider many parameters. The algorithm can customize easily to support multiple networks and optimize parameters. However, the

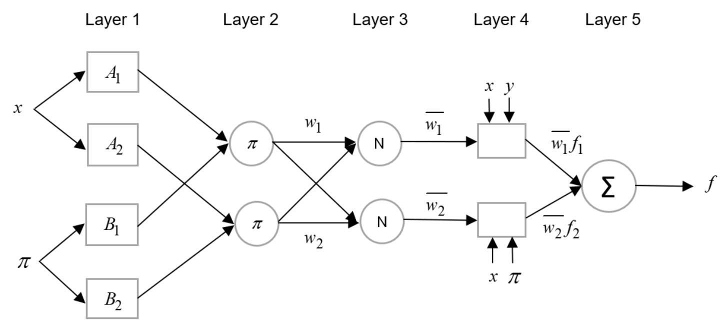

Figure 1: Adaptive Neuro-Fuzzy Inference System.

disadvantage of the fuzzy logic method is that it does not have a self-learning process for restructuring, which the system is determined by experts [1].

The handover decision process using fuzzy logic (FL) compared with fuzzy rule-based artificial neural network (ANN) in the design and development to support frequent handover in light-fidelity (Li-Fi) and wireless-fidelity (Wi-Fi) networks. Input parameters such as the instantaneous signal to interference noise ratio (SINR), received signal strength, average SINR and user velocity. From the experimental results, an accuracy test of 2 algorithms, the fuzzy logic was more successful in handover than the fuzzy rule-based ANN. However, the disadvantage is that decisions based on fuzzy logic can appropriate decisions based on rules. Meanwhile, the efficiency of fuzzy rule-based ANN was simulated using trained data from the fuzzy rules which have more recognition as a result this algorithm has little error when handover decisions [2].

Using a vertical handover mechanism to select the best position. Network selection affects to high quality of service. It provides a suitable network during handover, users could stay on networks for a long time and reduce the frequency of handovers such as the ping pong effect, that is multiple handoffs between two devices. This has an impact on user quality. The author solves a problem using network selection with QoS to define network rankings of significance for each algorithm [3]-[5].

Therefore, in this paper, the hybrid handover decision is using the neuro-fuzzy method, which is a combination of neural network and fuzzy logic to use the vertical handover decision for communication with the fifth generation of wireless networks more efficiently.

3 NEURO-FUZZY LOGIC ALGORITHM

3.1 Adaptive neuro-fuzzy inference system (ANFIS)

This model applies an artificial neural network system (ANN) which has advantages in learning but cannot explain the acquisition of decisions. It is working with Fuzzy Logic that qualifies like humanity but is unable to learn automatically. Before entering the process, input is converted by the fuzzy logic and entered the ANN for further processing. Using the rule of Sugeno fuzzy model or Fuzzy If-Then Rules to display data sets and relationship between input and output. The model consists of five layers. Within layer, layer 2, layer 3 and layer 5 are fixed while layer 1 and layer 4 are adaptive. Additionally, the adaptable parameters of the network are learned and improved to reduce the error between actual and desired output [6]-[7].

In Fuzzy If-Then Rules, IF is the premises parameter and THEN is the consequential parameter. For input x, y, fuzzy set A1, A2, B1, B2, defuzzification layer parameter p1, p2, q1, q2, r1, r2 and output f, the rules can be described as

$$Rule\,1 : If\ x\ is\,A1\ and\ y\ is\ B1,\ then\ f1 = p1x + q1y + r1 \quad (1)$$

$$Rule\,2 : If\ x\ is\,A2\ and\ y\ is\ B2,\ then\ f2 = p2x + q2y + r2 \quad (2)$$

In Figure 1 represents the architecture of ANFIS model with two inputs. The procedure of each layer can be expressed as

Layer 1: The first layer of the ANFIS model is called the fuzzification layer or input membership function. Nodes in this layer are adaptive nodes. For input x, and premise parameter set $\{a, b, c\}$ that are changed by the triangular function as depicted in (9), so outputs of this layer are the premise parameters.

$$O_{1,i} = \mu_{Ai}(x) = triangular\,(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{x-b}\right), 0\right) \quad (3)$$

Layer 2: The second layer is called the fuzzy rule layer. The membership value calculated from the fuzzification layer is used to calculate the firing strength by the sum of membership. The result is called Normalized Firing Strength (W). Nodes in this layer are fixed nodes and each node follows the rule of Sugeno fuzzy model. For the value of membership $\mu A, \mu B$ and the firing strengthw_i, the output of the layer can be calculated as

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(x) \quad for\ i = 1, 2 \quad (4)$$

Layer 3: The third layer is called is the normalization layer. Nodes in this layer are fixed nodes, node i represents the proportion of fuzzy rule when compared w_i with the total fuzzy rule. So, the normalized firing strength is calculated against the sum of rules. For firing strength w_1, w_2 and normalized weight $\bar{w}_i$, the information of this layer can be expressed mathematically as

$$O_{3,1} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad for\ i = 1, 2 \quad (5)$$

Layer 4: The fourth layer is called the defuzzification layer. In this layer, using a linear polynomial equation to define the weighted values of rules in each node. Nodes in this layer are adaptive nodes. For the normalized weight $\overline{w_i}$, the parameters p_i, $q_i$and r_i are adjusted using the recursive least square estimator (RLSE), the output can be determined as

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i} \left(p_i x + q_i y + r_i \right) \quad for\, i = 1, 2 \tag{6}$$

Layer 5: The last layer is called the summation layer which has a single node. Combine results from the defuzzification layers to get the output. Nodes in this layer are fixed nodes. The total output can be calculated as

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i \frac{w_i}{f_i}}{\sum_i w_i} \tag{7}$$

3.2 Fuzzy Membership Function

The characteristic of membership function is significant in the design of the fuzzy inference system (FIS). The membership functions have many shapes, which have different shapes such as triangular function, trapezoidal function, gaussian membership function, etc.

The choice of membership function depends on the data set used. For this project, we chose the triangular membership function. It is a commonly used function that is simple but efficient as it consists of two linear equations, so the membership value can be found from these linear equations. There are three variables $\{a, b, c\}$ where the lower limit is$a$, the upper limit is c, and the value b is $a < b < c$ and the equation of triangular membership function can be represented as [8]

$$triangular\,(x; a, b, c) = \begin{cases} 0\ ;\ x \le a \\ \frac{x-a}{b-a}\ ;\ a < x \le b \\ \frac{c-x}{c-b}\ ;\ b < x < c \\ 0\ ;\ x \le c \end{cases} \tag{8}$$

The alternate equation is shown in the form of min and max.

$$triangular\,(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right) \tag{9}$$

4 VERTICAL HANDOVER DECISION WITH NEURO-FUZZY LOGIC APPROACH

In Figure 2a, the handover decision process. Start by checking the user's position. Firstly, the users are within the WLAN area. In this case, check the following conditions. The received signal strength of WLAN (RSS_{WLAN}) is less than or equal to the received signal strength of WLAN threshold (RSS_{TH_WLAN}) and the dwell time of WLAN (DT_{WLAN}) is greater than the dwell time of threshold (DT_{TH}). If it is true as mentioned above, the handover decision by Neuro-Fuzzy of WLAN is operated and if it is false the users do not handover.

In Figure 3 b, the users under the Mobile WiMAX area check nearly above condition. The received signal strength of Mobile WiMAX (RSS_{WiMAX}) is less than or equal to the received signal strength of Mobile WiMAX threshold (RSS_{TH_WiMAX}) and the dwell time of Mobile WiMAX (DT_{WiMAX}) is greater than the dwell time of threshold (DT_{TH}). If true, the handover decision by Neuro-Fuzzy of Mobile WiMAX is operated and if it is false the users do not handover. Finally, the users are different from the above cases. Check the conditions of LTE-A. The received signal strength of LTE-A ($RSS_{LTE\text{-}A}$) is less than or equal to the received signal strength of LTE-A threshold ($RSS_{TH\_LTE\text{-}A}$) and the dwell time of LTE-A ($DT_{LTE\text{-}A}$) is greater than the dwell time of threshold (DT_{TH}). If it true, the handover decision by Neuro-Fuzzy of LTE-A is operated and if it false the users do not handover. Finally, when the handover decision by neuro-fuzzy of heterogeneous wireless networks is finished. Check the target of channel is empty and forward the data to handover. On the other hand, the data is blocked and completed.

5 SIMULATION ANALYSIS

5.1 Simulation environment

The received signal strength for networks can be determined as follow [9]

$$RSS(d) = P_t - PL(d) \tag{10}$$

where P_t is the transmit power in watt (w) and $PL(d)$is the path loss at distance (d) in meter (m) between a mobile user and a base station. In this paper, the authors use P_t= 1 watt.

In LTE-A, the path loss at distance (d) can be calculated as

$$PL(d)_{dB} = S + 10n \log(d) + \chi_\sigma \tag{11}$$

where S represents the path loss constant, n is the path loss exponent and $\chi_\sigma$denotes the shadow fading effect which is the zero-mean Gaussian distributed random variable with standard deviation σ(dB). In this paper, the authors used S = 19, n = 3.5 and χ_σ = 36 dB, respectively.

In Mobile WiMAX, the path loss is used the Cost-231 Walfish-Ikagami model [11] that is defined as

$$PL(d)_{dB} = 42.6 + 26 \log(d) + 20 \log(f) \tag{12}$$

where f is the operating frequency (MHz) and d is the distance from a mobile user to a base station (m)

Finally, received signal strength of WLAN can be calculated as

$$RSS(d)_{dBm} = 10 \log \left(\frac{100}{(39.37d)^\gamma} \right) \tag{13}$$

where γ intend the environmental factors of transmission which is set to 2.8.

5.2 Simulation parameter

The author has determined the range of 3 categories of wireless networks namely WLAN, Mobile WiMAX and LTE-A, that are used to estimate the received signal strength. Randomly selecting the user's position and determining the signal radius from the base station. The authors set the radius of WLAN, Mobile WiMAX and LTE-A networks to be 100 meters, 1,000 meters and 2,000 meters, respectively. The user's position was randomly from a point assigned in the plane of x-axis within 0-5,000 meters and The plane of y-axis within 400-5000 meters, providing a position covering all 3 networks as illustrated in Figure 4.

5.3 Simulation performance

The received signal strength in each network is compared. The user node can determine which direction to move within the range set

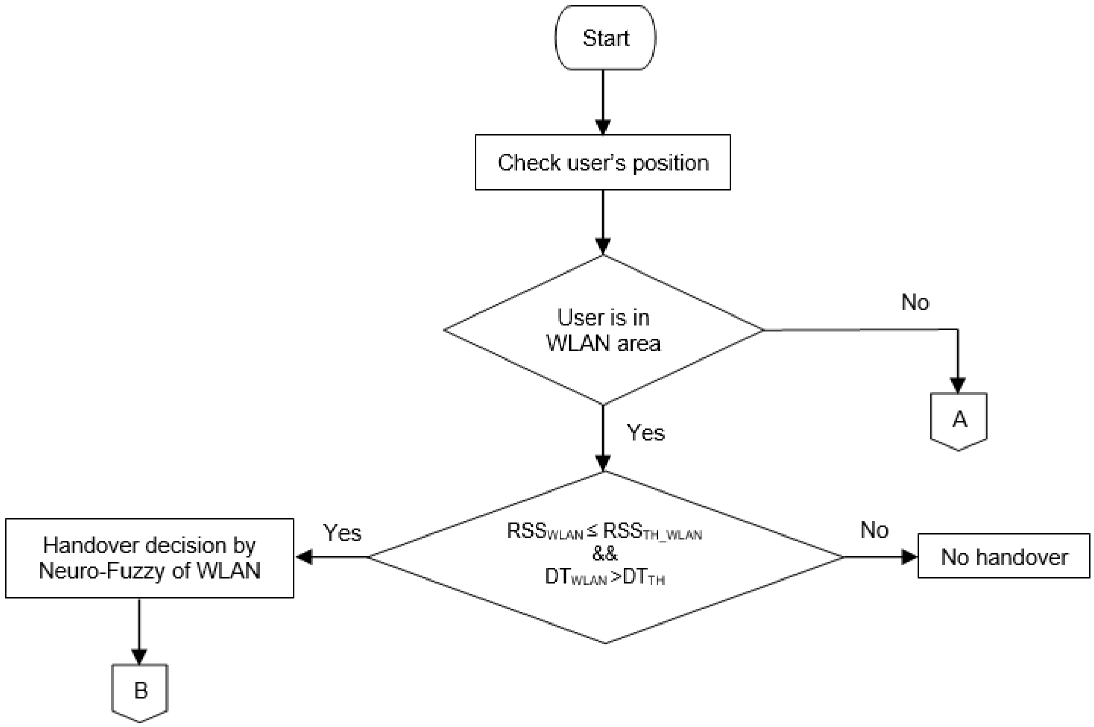

Figure 2: a Hybrid handover decision using neuro-fuzzy logic.

Table 1: Simulation Network Parameters

Networks	WLAN	Mobile WiMAX	LTE-A
Received Signal Strength (dBm)	-81 to -25	-161 to -120	-140 to -80
Mobile Speed (m/s)	5	139	19
Bandwidth (MHz) [10]	40	10	20

Table 2: Received signal strength interval.

Networks	Low (dBm)	Medium (dBm)	High (dBm)
WLAN	[-81, -58.5)	[-65.5, -43.5)	[-47.5, -25]
Mobile WiMAX	[-161, -145)	[-149, -132)	[-136, -120]
LTE-A	[-140, -118)	[-122, -98)	[-102, -80]

by random position. A threshold value prevents connection quality from decreasing while moving through the overlap area. The received signal strength of networks, which are the strongest is the target network and enters this into the handover decision process. In this process, if the received signal strength is less than a threshold value, that leaves the current network, causing unnecessary handover. Therefore, set dwell time to help ensure that user nodes do not return to the before network. The received signal strength is determined by finding the appropriate range for each network and calculating from the equations can be demonstrated as

Table 3: Mobile speed interval.

Low (m/s)	Medium (m/s)	High (m/s)
[5,54)	[47, 97)	[90, 139]

Table 4: Bandwidth interval.

Low (MHz)	Medium (MHz)	High (MHz)
[10, 23)	[18, 32)	[27, 40]

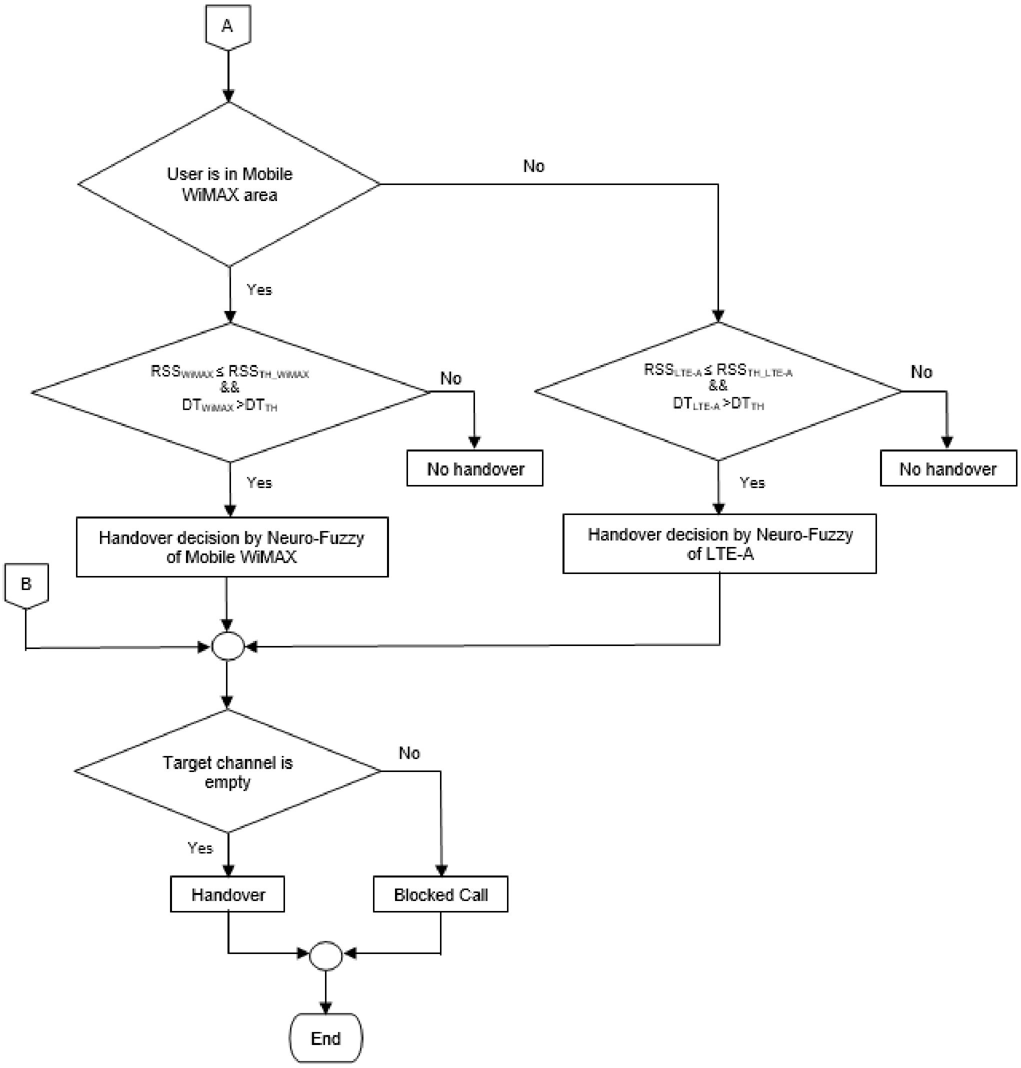

Figure 3: b Hybrid handover decision using neuro-fuzzy logic.

6 RESULTS

The number of handovers with neuro-fuzzy is less than using the back-propagation neural network and the fuzzy logic, respectively. The neuro-fuzzy has more recognition process than other methods which is the cause of less error value. This is consistent with result as shown in Figure 5, that the neuro-fuzzy method has a smaller number of handovers than other methods. On the contrary, there are increasing users.

Moreover, the number of blocked calls with neuro-fuzzy is less than using the back-propagation neural network and the fuzzy logic, respectively. The neuro-fuzzy assists in reducing blocked calls allowing users to communicate more efficiently and continuously between heterogeneous wireless networks without being congested during handover decisions can be depicted as Figure 6.

7 CONCLUSION

In this paper, the author presented the vertical handover using neuro-fuzzy that combined the artificial neural network and the fuzzy logic with triangular function for recognition process and error performance is 0.001. Input parameters such as the received signal strength, bandwidth and mobile speed enter handover decision using neuro-fuzzy that improves user communication efficiency and service quality. From research results, it was found that neuro-fuzzy reduces the number of handovers and handover of blocked calls more than other methods. In conclusion, the neuro-fuzzy logic method is the best when compared with fuzzy logic and back-propagation neural network. Therefore, this proposed process makes users satisfied with the quality of service (QoS) and the best connection at anytime and anywhere.

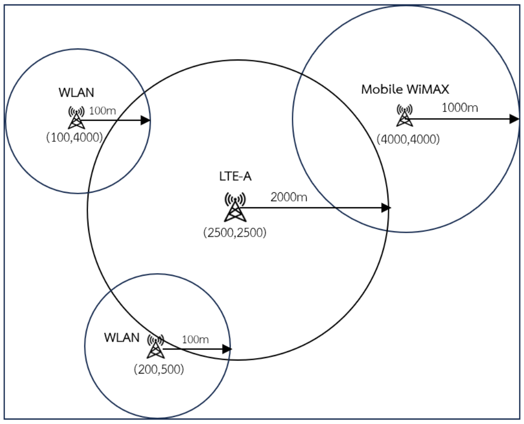

Figure 4: Heterogeneous wireless networks.

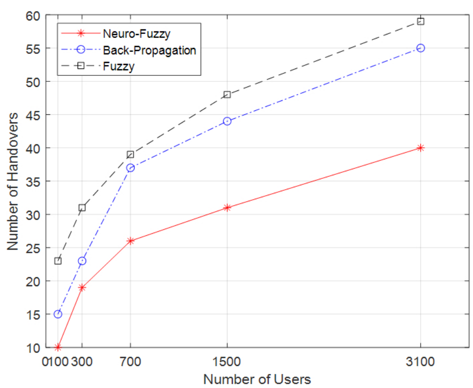

Figure 5: Number of users vs number of handovers.

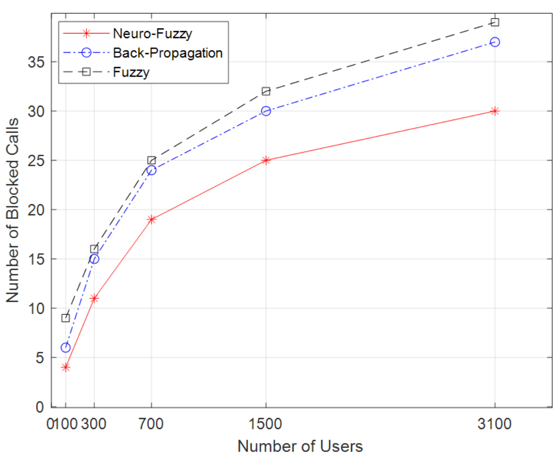

Figure 6: Number of users vs number of blocked calls.

8 CITING RELATED WORK

This section cites a variety of journal [6] and conference [1–5, 7–11]

ACKNOWLEDGMENTS

The authors would like to thank the Faculty of Engineering and the Graduate School, Srinakharinwirot University for supporting grant (Master's Degree).

REFERENCES

[1] Siddharth Goutam and Srija Unnikrishnan. 2019. QoS based Vertical Handover Decision Algorithm using Fuzzy Logic. In Proceedings of 2019 International Conference on Nascent Technologies in Engineering (ICNTE). IEEE, Navi Mumbai, India, 1–7. https://doi.org/10.1109/ICNTE44896.2019.8945953

[2] Jaafaru Sanusi, Sadiq Idris, Steve Adeshina, Abiodun Musa Aibinu and Ibrahim Umar. 2020. Development of Handover Decision Algorithms in Hybrid Li-Fi and Wi-Fi Networks. In Proceedings of the 3rd International Conference on Intelligent Sustainable Systems [ICISS 2020]. IEEE, Thoothukudi, India, 1232–1239. https://doi.org/10.1109/ICISS49785.2020.9316116

[3] Aridegbe.A.A.Ipaye, Israa.I.O.Ahmed, Dimitrios.N.G.Mitropoulos, Ali.M.A.Ibrahim and Sami Abbas Nagar. 2018. Mathematical Model Implementation of Vertical Handover Network Decision Algorithms in Heterogeneous Network Based On QoS Parameters. In Proceedings of 2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE). IEEE, Khartoum, Sudan, 1-6. https://doi.org/10.1109/ICCCEEE.2018.8515776

[4] Sheela Priyadharshini, Jayasurya Venugopalan, Murad Khan and Kijun Han. 2015. A multi-threshold triggering and QoS aware vertical handover management in heterogeneous wireless networks. In Proceedings of 2015 International Conference on Soft-Computing and Networks Security (ICSNS). IEEE, Coimbatore, India, 1-5. https://doi.org/10.1109/ICSNS.2015.7292405

[5] Sassi Maaloul, Mériem Afif and Sami Tabbane. 2016. Handover Decision in Heterogeneous Networks. In Proceedings of 2016 IEEE 30th International Conference on Advanced Information Networking and Applications (AINA). IEEE, Crans-Montana, Switzerland, 588-595. https://doi.org/10.1109/AINA.2016.33

[6] J.-S.R. Jang and Chuen-Tsai Sun. 1995. Neuro-fuzzy modeling and control. Proceedings of the IEEE, Vol. 83. Califomia, Berkeley, 378-406. https://doi.org/10.1109/AINA.2016.33

[7] Monika Kabir and Mir Md. Jahangir Kabir. 2021. Fuzzy membership function design: An adaptive neuro-fuzzy inference system (ANFIS) based approach. In Proceedings of 2021 International Conference on Computer Communication and Informatics (ICCCI -2021). IEEE, Coimbatore, India, 1-5. https://doi.org/10.1109/ICCCI50826.2021.9402633

[8] Muhammad Hamza Azam, Mohd Hilmi Hasan, Saima Hassan and Said Jadid Abdulkadir. 2020. Fuzzy Type-1 Triangular Membership Function Approximation Using Fuzzy C-Means. In Proceedings of 2020 International Conference on Computational Intelligence (ICCI). IEEE, Bandar Seri Iskandar, Malaysia, 115-120. https://doi.org/10.1109/ICCI51257.2020.9247773

[9] Sunisa Kunarak and Tanin Duangchan. 2021. Vertical Handover Decision based on Hybrid Artificial Neural Networks in HetNets of 5G. In Proceedings of 2021 IEEE Region 10 Symposium (TENSYMP). IEEE, Jeju, Korea, 1–6. https://doi.org/10.1109/TENSYMP52854.2021.9550952

[10] Sunisa Kunarak. 2016. A Dynamic Channel Allocation Algorithm Based on Back-Propagation Neural Network for Vertical Handover in HetNets. In Proceedings of 2016 UKSim-AMSS 18th International Conference on Computer Modelling and Simulation (UKSim). IEEE, Cambridge, UK, 287-292. https://doi.org/10.1109/UKSim.2016.

[11] S.F.Hamim and M.F.Jamlos. 2014. An overview of outdoor propagation prediction models. International Journal of Scientific & Engineering Research, In Proceedings of 2nd International Symposium on Telecommunication Technologies (ISTT). IEEE, Langkawi, Malaysia, 385-388. https://doi.org/10.1109/ISTT.2014.7238240